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Understanding Society

Umbrella Branding in Pharmaceutical Markets*

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Abstract Umbrella branding is a marketing practice whereby multi-product firms leverage their reputation across different product categories. This paper investigates how advertising in the market of over-the-counter (OTC) drugs affects the decision to buy prescription drugs from a promoted brand name. I exploit specific characteristics of market regulation in Germany to identify the effect of advertising and find positive effects of umbrella branding on sales of prescription drugs. Umbrella branding results in market expansion, particularly for generic firms which invest in OTC drug advertising. If the effect leads to more consumers of generic substitutes or to more patients in undertreated therapeutic areas, market expansion can have a positive effect on welfare.

Key words: umbrella branding, regulation, empirical io, pharmaceuticals, marketing
JEL Codes: L13, L51, I11, I18, M37, D22, C18

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1 Introduction

Umbrella branding extends the reputation of multi-product firms across unrelated product categories. The marketing practice of linking reputation across products or services is particularly relevant for experience goods, such as in health care markets. For example, consumers of pharmaceuticals are typically not well-informed about the quality (effectiveness) of the good; their awareness and quality perception may be influenced by the reputation of the firm. A common brand name that links products in the minds of consumers is beneficial for firms because it allows them to send more credible signals about quality (Choi, 1998; Nelson, 1974; Bagwell, 2007). Deviations from producing high quality, even for one product, result in profit losses for the whole product portfolio.[1]

The empirical problem in identifying the effect of umbrella branding is to isolate the causal effect of the reputation of a brand name across markets. Particularly problematic are confounding factors interfering with the spillover effect, such as direct advertising or other supply-side factors like quality (Bronnenberg et al., 2012; Dubois et al., 2014). To address these empirical issues, I exploit an institutional detail of the German pharmaceutical industry, a market with strict advertising regulations for prescription drugs and more liberal regulation for OTC drugs.[2] The brand name spillover from OTC to prescription drugs works purely through reputation since information provision about prescription drugs is prohibited by law. The setting isolates the effect of umbrella branding on sales net of any other marketing effects.[3]

I investigate how the probability of buying a prescription drug varies with the exposure of consumers to non-prescription drug advertising. An instrumental variable approach addresses issues from endogenous choices of advertising. In particular, I exploit the exogenous variation in the timing of the advertising of OTC drugs. Data on the advertising of OTC drugs show seasonal patterns and peaks of expenditures in each November (Nielsen

[1] Tirole (1996) shows that employees of a manufacturer also have incentives to maintain a high quality and, thus, the reputation of the brand name.

[2] Consumer-directed advertising is not allowed in Germany as in any other OECD country with the exception of the US and New Zealand. In the US, several academic medical centers have implemented policies to ban the exposure of doctors to advertising (detailing) as an effort to address conflicts of interest (Larkin et al., 2017). On the contrary, OTC drug advertising aimed at patients is legal in many jurisdictions (OECD, 2010).

[3] For example, the multi-product firm *Bayer* sells several prescription and OTC drugs, such as *Adempas or Aspirin*. Each package in the portfolio depicts the brand logo (compare Appendix A (5)).

Media, 2012). The seasonality in advertising for OTC drugs correlates with the season of colds and the flu, two common categories in the OTC drugs market.

Seasonal consumption patterns do not affect sales in my empirical analysis, since it focuses on prescription drugs to treat chronic diseases (diabetes, epilepsy, and Alzheimer's disease). In a reduced-form sales equation, I investigate the effects of advertising OTC drugs on the sales of prescription drugs. I measure reputation by the stock of past advertising expenditures, which also captures the long-lived effects of the advertising on consumption patterns. My results indicate positive spillover effects of advertising of OTC drugs on prescription drug demand.

A structural model complements the empirical analysis and quantifies the economic effects more precisely. I estimate prescription drug demand and allow advertising spillovers from the OTC drug market to affect the utility of the consumer (Berry et al., 1995). Using data from the therapeutic market for Alzheimer's disease drugs in Germany, I estimate that consumers place a positive value on OTC drug advertising. On the supply side, I assume Bertrand-Nash pricing of multi-product firms and simulate new optimal prices and quantities in the counterfactual equilibrium without advertising spillovers. My simulation shows that umbrella branding expands the market for AD drugs, i.e., the share of annually treated patients increases by about 10 percent. In particular, generic manufacturers expand their sales more than originators.[4] The results are driven by the larger stock of advertising expenditures of generic manufacturers in the OTC drug market, on average €7.2m, compared to an average of €2.26m by originators.

The literature helps to explain the different responses of the two firm types to advertising. First, advertising allows generic manufacturers to inform patients about alternative brands in formerly monopolistic markets (Königbauer, 2007; Hurwitz and Caves, 1988), and it overcomes brand loyalty and switching costs (Shum, 2004; Crawford and Shum, 2005). Some generic firms differentiate their products through advertising, a strategy to avoid price competition among generics (Berndt and Newhouse, 2012; Reiffen and Ward, 2007). Second, originators advertise so as to differentiate their products from therapeutic alternatives or to respond to generic entry (Rizzo, 1999; Bhattacharya and Vogt, 2003; Caves et al., 1991; EUC, 2009).

[4] I define drug manufacturers as originators who invest in R&D and generic firms who bring copies of no-longer-patented drugs to the market. In addition, European trade policies make imported versions of originator drugs available. In my paper, all drugs can advertise and accumulate brand reputation.

Advertising spillovers from unregulated to regulated markets can pose a threat to the health status of consumers if, for example, umbrella branding leads to misguided drug choices (FDA, 2014; ISMP, 2015). Regulation of pharmaceuticals is fragmented in the US: the *Federal Trade Commission* (*FTC*) oversees OTC drugs and the *Food and Drug Administration* (*FDA*) prescription drugs. Thus, the efficiency of regulation in pharmaceutical markets could benefit from more coordinated policies. The effects of advertising spillovers on social welfare, however, are difficult to quantify and depend on market characteristics. If patients of under-treated diseases, such as Alzheimer's disease, receive more medications, advertising spillovers would have a positive effect. In contrast, market expansion through advertising can be harmful for over-prescribed medications, such as opioids (Alpert et al., 2017).

My results are more general. Indeed, umbrella branding and advertising regulation are also relevant in other industries. For example, regulators implement advertising bans to protect consumers in markets such as cigarettes (Chaloupka and Warner, 2000) or junk food (Dubois et al., 2014). From a policy perspective, umbrella branding poses challenges to regulators if firms bypass advertising restrictions by linking reputation across regulated and unregulated markets. An example is the beer industry in India: since advertising for alcohol was banned it instead advertises soft drinks and drinking water (Prasad, 2009).

Related Literature – Theoretical work emphasizes the role of umbrella branding when introducing a new product (Choi, 1998; Wernerfelt, 1988), in markets with repeated purchases (Cabral, 2000), and as a substitute for external certificates (Hakenes and Peitz, 2009). Empirical work identifies umbrella branding in industries other than pharmaceuticals (Erdem, 1998; Balachander and Ghose, 2003; Erdem and Sun, 2002; Erdem, 1998), e.g., in the form of celebrity endorsement on book sales of the same author (Garthwaite, 2014). My article estimates a structural model to quantify the effects of umbrella branding and proposes a new identification strategy for advertising spillovers.

Ling et al. (2002) analyses how the marketing of a prescription drug affects the subsequent sales of drugs after its status has switched from prescription to non-prescription (Rx-to-OTC switch). The authors find positive spillover effects of prescription drug marketing earlier in the life cycle of drugs on sales after the Rx-to-OTC switch. My work does not investigate Rx-to-OTC switches and proposes the utilization of institutional characteristics outside the US to isolate the effect of reputation from other marketing

efforts. Various articles on pharmaceutical markets find mostly positive effects of advertising on drug demand and market shares (Lakdawalla et al., 2013; Avery et al., 2012; Ching et al., 2015; Iizuka, 2004; Ling et al., 2002). Several authors investigate advertising spillovers in pharmaceutical markets, e.g., Shapiro (forthcoming) estimates the positive effects from firm-specific advertising on the market level. Lakdawalla et al. (2013) find that the introduction of Medicare Part D, the US federal drug insurance program for the elderly, increases advertising expenditures which affects drug demand outside the Medicare program. Authors of the medical literature investigate the effects of spillovers on compliance (Wosinska, 2005; Donohue et al., 2007) and on doctor visits (Iizuka and Jin, 2007). My focus on the spillovers of the advertising of OTC drugs complements earlier work by emphasizing a new dimension of umbrella branding.

Although the empirical IO literature offers models that emphasize consumer heterogeneity (Berry et al., 1995; Nevo, 2001), there are relatively few applications to the complex and diverse market structures of pharmaceuticals. Notable exceptions are Kaiser et al. (2014) who analyze a reference price policy in Denmark, Dubois and Lasio (2014) who estimate the economic effects of price constraints in France, Lasio (2015) who estimates the impact of de-listing from insurance coverage, (Duso et al., 2014) who quantify the effects of parallel imports, and work by Dunn (2012) and Dutta (2011) on pharmaceutical innovations. My work models advertising as a characteristic and simulates a ban on advertising to quantify the economic effects of umbrella branding.

2 Institutional Setting and Umbrella Branding

Germany, like all European countries, prohibits prescription drug marketing toward patients. Regulation, however, does allow OTC drug advertising which was 12.6 percent of sales in 2010 in Germany (Nielsen Media, 2012). TV aired the most advertising (56%) and newspapers (34%). The product categories with the most advertising expenditures in 2011 are cough and cold remedies (€141m), analgesics (€108m), and relaxant agents (€81m) (Nielsen Media, 2012).

OTC drugs are available without prescriptions and patients choose from the shelf space or after expert advice from the pharmacist. OTC drugs are behind-the-counter products, i.e., are only available in pharmacies. The similarity of the place and procedure in buying OTC and prescription drug allows us to study effects at the border of the two markets.

In Germany, all approved prescription drugs are reimbursed by the public health insurance. It covers about 70 million insurees or about 85 percent of the total population (BMG, 2015). In contrast to the US, insurance plans do not differ among insurees[5] and the providers are directly reimbursed for products and services. Supermarkets or physician offices do not dispense drugs in Germany. Patients co-pay 10 percent per package, with a minimum of €5 and a maximum of €10. There are no deductibles or coverage gaps in the insurance plans. A uniform incentive and payment scheme for all pharmacists and physicians across Germany mitigates agency problems associated with third-party payers. Physicians are free in their drug choices and can either prescribe a product (and package size and strength) or an active ingredient. Reimbursement of physicians is independent of their prescription behavior. Neither insurance policies nor pharmacists can overrule the decision of the physician (aut-item regulation).[6] If the physician prescribes a molecule, the pharmacy has to offer one of the three cheapest products. Margins of pharmacists are regulated as a fixed fee plus 3 percent of the list price. Margins of wholesalers are regulated, too, and provide disincentives for stock-piling of pharmacies. Until 2011, firms were free to set prices and the public health insurance reimbursed the full list price of the drug. In some therapeutic markets, reimbursement policies set incentives for firms to decrease the price of generic drugs, e.g., reference prices or co-payments.

In Germany, promotional activities for prescription drugs comprise visits of sales representative to physicians (detailing), free samples, and sponsored marketing conferences. While free samples are a pure economic incentive, detailing and conferences might provide physicians with information (Ching and Ishihara, 2010). Earlier work shows that detailing may have business stealing effects, while consumer-directed advertising result in market-expansion (Ling et al., 2002; Iizuka, 2004; Iizuka and Jin, 2007; Ching et al., 2015).[7] I do not observe detailing and I use instruments for consumer-directed advertising in OTC drug markets to address the issues of the omitted variable.[8]

[5]Patients may augment their uniform public health plan with a private health plan. Public health plans, however, cover nearly all the pharmaceutical expenses of prescription drugs.

[6]Physicians face a non-binding prescription cost benchmark with neighboring colleagues. Physicians, however, renegotiate the benchmarks individually and regulators enforce them poorly (Schwermann et al., 2003). I assume that the prescription benchmark is a weak incentive for physicians to prescribe lower-priced pharmaceuticals.

[7]Mizik and Jacobson (2004) estimate that one additional prescription needs about 1.5–6.5 visits of a sales representative or 6.5–73 samples per visit.

[8]If observed consumer-directed OTC drug advertising and unobserved physician-directed prescription drug advertising (or their timing) are not perfectly correlated, the empirical findings are identified. To

Data on the therapeutic drug markets of diabetes, epilepsy, and Alzheimer's disease originate in the *Pharmascope National* database of IMS Health (2012). The data contains sales, prices, and characteristics of all products which were reimbursed by the German public health insurances between 2004 and 2011. Monthly firm-level, consumer-directed advertising expenditures from Jan 2002 to Dec 2010 originate from *Nielsen Media Germany* and include nationwide advertising in newspapers, journals, TV, radio, on billboards and the internet.

Table 5 presents the top 20 advertising firms over the sample period. Expenditures of firms span from €404m to €40m and total market expenditures were €5.6bn. The sample includes eight originators that advertise OTC products, e.g., *Pfizer* or *GSK*, five generic firms that advertise their OTC products, e.g., *Hexal* or *ratiopharm*, and eight OTC firms that do not sell prescription drugs, for example, *MCM Klosterfrau*.

Figure 1 presents OTC drug advertising and prescription drug sales over time. Monthly advertising expenditures increase over time and show seasonal trends: expenditures peak in fall (November) at the beginning of the cold and flu season.[9] Advertising seems to be correlated with a seasonal demand pattern in the OTC market, a fact also emphasized by Ling et al. (2002). Waves of advertising are common in many industries and are referred to as a pulsing strategy, whereby advertising peaks within a few weeks and drops thereafter (Dubé et al., 2005).[10]

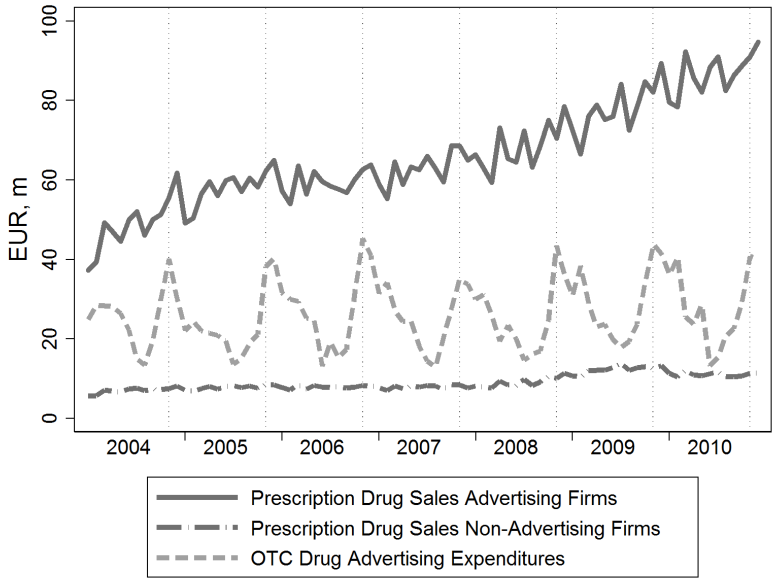
Figure 1 also shows sales of prescription drugs to treat epilepsy, diabetes, and AD differentiated by firms investing in OTC drug advertising (solid line) and non-advertising firms (dashed line). Over time, advertising firms gain market shares. The figure shows there are also increases in sales during or shortly after advertising peaks and signs of inter-temporal substitution, since sales for advertising brands decrease after the peak. The sales peaks are clearer between 2004 and 2007 and fuzzier toward the end of the observation period. Patients seem to test drugs which invest in advertising during or after the advertising peak periods. The upward trend of advertising drugs indicates that some

my knowledge, no study of the pharmaceutical industry reports seasonality in detailing: a large sector inquiry of the European Union reveals market entry and life-cycle management of drugs as drivers of detailing (EUC, 2009). Furthermore, a study of ACE inhibitor on diuretics in Canada from 1993 to 1999 does not find any seasonal peak in detailing, e.g., Figure 1 in Ching and Ishihara (2012).

[9] A second, smaller peak occurs in spring (March), a common season for hay fever and colds.

[10] Individual-level purchase decisions and advertising exposure, e.g., number and length of consumed commercials, would allow me to identify the effect of advertising spillovers directly. I assume an evenly distributed advertising exposure which is constant over time and media exposure to be exogenous, e.g., patients who search for prescription drug information are equally exposed to OTC advertising.

Figure 1: Prescription Drug Sales and OTC Drug Advertising



Notes: The graph shows monthly prescription drug sales for firms that invest in OTC drug advertising and for firms that do not advertise OTC drugs from Jan 2004 to Dec 2010, and advertising expenditures in the OTC drug market over the same period. Vertical lines indicate Novembers, the month when advertising peaks each year. For the graphical depiction, firms are considered to be non-advertisers if their cumulative advertising expenditures do not exceed the 25th percentile, i.e., €35,000 over 7 years. Data: IMS Health and Nielsen Media Research.

become loyal consumers over the observation period. The pairwise correlation coefficient of sales and advertising is $.196^{***}(< .01)$.

I estimate sales of product j in time t, S_{jt}, as a function of advertising of firm f, a_{ft}:

$$\ln S_{jt} = \omega \ln a_{f(j)t} + \psi_t + \chi_j + \epsilon_{jt} \tag{1}$$

where the function $f(j)$ indicates the firm f selling the product j. ψ_t denote time fixed-effects and ϵ_{jt} are error terms. Product fixed-effects, χ_j, control for time-invariant product characteristics and help to identify the mean effect of advertising on sales (Bronnenberg and Dubé, forthcoming). Because consumers keep marketing activities in mind, firm reputation possibly depends on all advertising expenditures in past periods (Lakdawalla et al., 2013; Berndt et al., 2003). I construct advertising stocks as the depreciated expenditure of past periods plus current advertising expenditures (Dubois et al., 2014). Equation 2 models the advertising vector of firm f in period t as:

$$a_{ft} = \lambda a_{ft-1} + e_{ft} = \sum_{\tau=0}^{t} \lambda^{\tau} e_{ft}, \tag{2}$$

where stocks of advertising from the last period, a_{ft-1}, depreciates with rate λ and e_{ft} denotes investments in advertising in period t. Since depreciation rates are not observed, I follow Lakdawalla et al. (2013) and run a grid search for the optimal depreciation rate. I therefore estimate market share equation 1 and choose the best model fit, i.e., minimal mean squared errors. I find a yearly depreciation rate of 42.5 percent on advertising which is in range of previous research.[11]

I instrument advertising spillovers by exploiting the timing of seasonal illnesses, like the flu. I expect the seasonality to be correlated with OTC drug advertising (compare Figure 1) but to be independent of the prescription drug market. The seasonality of the

[11] Ling et al. (2002), Berndt et al. (2003), and Lakdawalla et al. (2013) find optimal depreciation rates between 30 percent per year to 13 percent per month. Alternatively, Dubois et al. (2014) and Azoulay (2002) assume a depreciation rate of 25 percent and 5 percent per month.

demand of OTC drugs is unlikely correlated with characteristics of demand of prescription drugs to treat chronic diseases. The stock of advertising measures the reputation of firms. Therefore, the instrument accounts for the stock of advertising by calculating a stock of months in which the firm was exposed to peak demand in markets of OTC drugs, i.e., stocks of past Novembers. Formally, I define a dummy variable of seasonality which equals one in November and zero otherwise. The variable on the firm-level captures the exposure of firms to high-advertising months. The sum over the seasonality dummy, depreciated with the optimal rate for advertising, results in my instrument, the stock of seasons. The instrumental variable approximates the distance to previous Novembers. Both measures – season and stock of season – are independent of the error terms of sales of prescription drugs in Equation 1. Since seasonality is correlated with monthly advertising, the stock of seasons is correlated with the stock of advertising. In a next step, I interact the instrument with the potential exposure of each firm to the advertising of OTC drugs. To proxy for the number of OTC drugs per firm, I extract information on the portfolios of OTC drugs from the firms' websites and create a dummy (=1 if OTC drugs in the portfolio). Tables 1 and 7 show the strong correlation of the instrument with the stock of advertising.

Table 1: Reduced-form Evidence of Advertising on Sales

	Total Market Sales	
	OLS	IV
Advertising (stock, €, ln)	.05***	.06***
	(.01)	(.02)
Product FE	yes	yes
Time FE	yes	yes
N	31,538	31,538
R^2_{adj}	.86	.86
	First-stage	
Season (stock, ln)		6.23***
		(.48)
$F-test$		164

Notes: The columns present the effect of advertising (stock) on sales in quantities (daily doses). The instrument for advertising stocks are the stocks of season (column IV). The second part present the coefficient from the first stage. Constants are not reported. Standard errors are clustered at the product level and presented in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 1 presents results for the therapeutic markets of oral anti-diabetics, anti-epileptic, and AD drugs. Sales, S_{jft} are measured in quantities (defined daily doses or DDD). The coefficients for the stock of advertising are positive and significant across the OLS estimation in column (OLS) and after controlling for endogeneity (column IV). I find that a 10 percent increase in the non-prescription drug advertising stock increases sales of prescription drugs by .5 percent. The results compare to estimates of the elasticities of direct-to-consumer advertising of 7.5 percent in the US. Direct advertising transmits information on products, molecules, and brand names (Berndt et al., 1995) and is expected to have a stronger effect than spillovers. The total effect of spillovers are most likely larger because firms can potentially realize spillovers in more therapeutic markets. Column (IV) also presents results of the first stage. The coefficient is positive and statistically significant. Also, the F-test is above the critical value (Stock et al., 2002).

3 Econometric Model

I estimate a random coefficient logit demand model (Berry et al., 1995) that accommodates advertising spillovers from OTC markets as a complementary characteristic. On the supply side, I assume oligopolistic competition and calculate elasticities, margins, and marginal costs. The counterfactual analysis calculates equilibrium outcomes – like price, quantities, and consumer surplus – in a market without advertising spillovers and compares it to the status quo equilibrium.

To investigate the economic effects of umbrella branding on one therapeutic market, the empirical analysis focuses on the prescription drug market for the Alzheimer's disease. Its descriptive statistics are similar to the total sample, i.e., the correlation of advertising expenditures and sales is $.312^{***}(< .01)$. Furthermore, the results of the reduced-form equation 1 for the AD drug market resemble the results for the total market.

3.1 Data

The market for Alzheimer's disease drugs in Germany included 106 different products and 54 firms between 2004 and 2010. The sample contains information on seven drugs from innovators, 45 imported innovative drugs,[12] and 54 generics. The market is com-

[12]Imported originator drugs (parallel imports) are the result of free trade and public pharmaceutical price regulation in the European Union (Duso et al., 2014).

prised of six molecules: *donepezil, galantamine, ginkgo biloba, memantine, piracetam,* and *rivastigmine*.[13] Two of the molecules are off-patent and four are patented.

Table 2 presents descriptive statistics by originator drugs, imports, and generics. The statistics show the importance of OTC advertising for generic drug manufacturers: on average, 67 percent of generic firms invest in advertising. The amount of advertising stock, however, differs substantially: originators possess €2.2m as stock of advertising and generic firms €7.3m. Importers possess less stock with an average of €70,000. Importing firms focus on the trade of (formerly) patented products and, to my knowledge, there is no import firm marketing OTC products.[14] Most drugs from originators and importers (71% and 76%) are sold in markets under patent protection. The market structure results in almost eightfold higher prices of drugs of originators than those of generic manufacturers. The latter face, on average, 26 competitors per molecule. In different strengths, the molecule *ginkgo biloba* is also available as an OTC drug (which is not eligible for reimbursement under the public health insurance). Patients receive a reimbursement for *ginkgo biloba* if they follow the same procedure as for a prescription drug: they obtain a prescription from the physician, hand their prescription to the pharmacist, and co-pay. Also, pharmacies receive the same reimbursement for prescribed *ginkgo biloba* as for all other prescribed drugs. Firms, however, could publicly advertise low-dosage versions of drugs that the public health insurance reimburses in a high-dosage presentation. I assume that high-dosage presentations are different products, find that advertising for non-prescription AD drugs is minor, and discuss results from a robustness check w/o *ginkgo biloba* in section 5.[15]

Table 5 indicates in column *AD Drug* which firm sells Alzheimer's disease drugs. The OTC firm *Klosterfrau* spends, on average, almost €5m per month on advertising, followed by the originators *Novartis* and the OTC firm *Schwabe*. Firms tend to adjust advertising to market dynamics and the table shows a large variance of advertising expenditure across

[13] All international clinical guidelines recommend the first-line pharmacological treatment options cholinesterase inhibitors (*donepezil, galantamine* and *rivastigmine*) and *memantine* (DGPPN (2015) for Germany; or Winslow et al. (2011) and Qaseem et al. (2008) for the US). German physicians frequently prescribe *Piracetam* and high-dosage *ginkgo biloba* for AD patients in Germany (DGPPN, 2015).

[14] In addition, some firms also import medical equipment which they might advertise sparsely. The expenditures include billboard advertising, for example, sponsoring local sporting events.

[15] Furthermore, status switches from prescription to non-prescription (*Rx-to-OTC switch*) are not a feature of the AD drug market.

Table 2: Summary Statistics by Type of Drug

Drug type	Originator	Import	Generic	All
N	588	1,547	3,107	5,242
Advertising [%]	48	47	67	59
	(50)	(50)	(47)	(49)
Advertising stock [€, m]	2.26	.07	7.30	4.94
	(4.74)	(.08)	(11.85)	(10.31)
s_{jt} [%]	7.80	.44	1.01	1.60
	(5.97)	(.91)	(1.80)	(3.33)
Price [€/DDD]	2.62	3.19	.42	1.49
	(1.5)	(2.12)	(.23)	(1.81)
Firm [N]	6.00	8.18	26.8	2.49
	(.00)	(3.08)	(4.05)	(9.89)
Patented [%]	71	76	-	30
	(45)	(43)	-	(46)

Notes: The table displays Alzheimer's disease drug data by type (originator, import, generic) from Jan 2004 to Dec 2010. Own calculations with data from IMS Health and Nielsen Media Research. Std. dev. in parentheses.

firms and over time. Some firms invest only in selected months. For example, the firm *Sandoz* has zero expenditure in some months while more than €2m in others.

3.2 Pharmaceutical Demand

Utility maximizing in pharmaceutical markets is not straightforward, demand structures are complex and involve multiple parties. For example, insurance policies define benefits and patients rely on the recommendations of physicians who might have their own preferences for particular brands or active ingredients. I assume that patients appreciate advice from experts in experience good markets (Hilger et al., 2011). They maximize utility jointly with their physician and pharmacist by selecting a drug (Carrera et al., 2017; Kesternich et al., 2015). Patients can influence their drug choice by, first, asking their doctors for a specific brand.[16] Second, patients could choose a particular brand (or

[16]Previous studies show that physicians' patterns to prescribe is driven by requests of patients (Kravitz et al., 2005). Reports from the US state that 78 percent of primary care physicians were asked by their patients for specific drugs which they had seen directly advertised (ISMP, 2015). Most likely, the effect is smaller for advertising spillovers. My model of advertising allows spillovers of the brand name,

package) in the pharmacy. Some patients with late-stage Alzheimer's disease may live in long-term care facilities. The main characteristics of drug demand, e.g., free choice of doctors and pharmacies (both may regularly visit nursing homes), are the same for all patients. Long-term care facilities in Germany cannot tender their drug demand, e.g., in preferred supplier contracts. Data on the product-level aggregates individual preferences of the demand side. The model estimates pharmaceutical demand from aggregate data and captures heterogeneous demand parameters with a random coefficient (Dubois and Lasio, 2014).

The decision of patient $i = \{1, ..., I\}$ to buy drug $j = \{1, ..., J\}$ is the result of utility maximization in time $t = \{1, ..., T\}$. Consumers maximize utility over bundles of characteristics including the stock of advertising expenditures of OTC drugs of firm f. The regulator prohibits prescription drug advertising in the German pharmaceutical market. However, patients consume the advertising of OTC drugs including information on brand names. Individual utility of patient i for product j in period t is defined as:

$$u_{ijt} = -\alpha p_{jt} + \sigma p_{jt}\nu_i + \gamma a_{f(j)t} + \zeta_j + \psi_t + \xi_{jt} + \epsilon_{ijt}, \tag{3}$$

where firm $f(j)$ sells products j. Price of product j is p_{jt}, ζ_j are time-invariant drug characteristics, ψ_t are market fixed-effects, ξ_{jt} are unobserved effects on utility, and ϵ_{ijt} are a consumer-product-specific error terms. The term $\sigma p_{jt}\nu_{ijt}$ captures individual disutility for prices. Advertising, $a_{f(j)t}$, enters as a state variable which consists of current and past advertising expenditures discounted by the optimal depreciation rate as described in Equation 2.[17] Prices, p_{jt}, are the prices of manufacturers per defined daily dose (DDD). Although consumers bear co-payments, a function of prices, the strategic variable of firms, physicians, health insurances, and pharmacists are prices. The random coefficient allows heterogeneous individual preferences for prices. Utility can be decomposed into an individual part, $\sigma p_{jt}\nu_i + \epsilon_{ijt}$, and the mean utility which is the same for all patients: $\delta_{jt} = -\alpha p_{jt} + \gamma a_{f(j)t} + \zeta_j + \psi_t + \Delta\xi_{jt}$. I control for time-invariant unobserved and observed

i.e., between drugs from the same firm but not to competitors' drugs. In industries where advertising spillovers contain information about the promoted product, spillovers can result in free-riding of competitors (Shapiro, forthcoming).

[17] My model is similar to Murry (2015) for automobile demand, Nevo (2001) for cereals, or Chintagunta (2002) for analgesics. Shapiro (forthcoming) and Dubois et al. (2014) show theoretical dynamic considerations.

drug characteristics and global shocks by product and time fixed-effects which redefines the unobserved part of utility as $\Delta\xi_{jt}$. Utility can be rewritten as:

$$u_{ijt} = \delta_{jt} + \sigma p_{jt}\nu_i + \epsilon_{ijt}. \tag{4}$$

Patients and physicians jointly maximize utility and the error terms ϵ_{ijt} are assumed to be independently and identically extreme value type I distributed.[18] The choice probability of drug j for consumer i at time t can be written as:

$$s_{ijt}(x, p, a; \theta) = \frac{\exp(\delta_{jt} + \sigma p_{jt}\nu_i)}{1 + \sum_J \exp(\delta_{jt} + \sigma p_{jt}\nu_i)}, \tag{5}$$

where $\theta = [\alpha, \beta, \gamma, \sigma]$. The assumption that ν is distributed with p.d.f. dP_ν allows to sum up individual choice probabilities as:

$$s_{jt}(x, p, a; \theta) = \int_{\nu_t} \frac{\exp(\delta_{jt} + \sigma p_{jt}\nu_{ijt})}{1 + \sum_J \exp(\delta_{jt} + \sigma p_{jt}\nu_i)} dP_\nu(\nu_t). \tag{6}$$

Section 3.3 describes in more detail the numerical solution of integral 6 and the role of unobserved characteristics, ξ_{jt}.

The logit model includes an option *to not buy Alzheimer's disease drugs* which is a composite outside good. The outside good also comprises the option to buy other treatments, such as cognitive training applications or personal memory training, and its normalized indirect utility is $u_{i0t} = \epsilon_{i0t}$. I calculate the total market size, M, by daily doses potentially consumed by all Alzheimer's disease patients per month.[19] The total market size increased from about 900k to 1.1m patients from 2000 to 2010 and results in about 30m potentially consumed daily doses per month.

[18] Logit demand models are special cases of the random coefficients models and assume $\sigma p_{jt}\nu_{ijt} = 0$. Section 4 presents mean utility estimates as a benchmark case ($u_{ijt} = \delta_{jt} + \epsilon_{ijt}$).

[19] Since age is the main risk factor for Alzheimer's disease, I collect historic age-specific prevalence rates from the German College of General Practitioners and Family Physicians (Degam, 2015) and the European Collaboration on Dementia Project (Eurocode, 2015). Using epidemiological data adds exogenous variation to our estimation. About 5 percent of the population aged over 65 and 20 percent of the population aged over 80 are diagnosed with dementia, whereof about 65 percent are associated with the Alzheimer's disease (Degam, 2015; Eurocode, 2015).

I argue that the potentially unobserved purchasing patterns of patients, for example, stock-piling or correlated purchases of prescription and OTC drugs, are not biasing my results: first, seasonal demand fluctuation are not a feature of the observed drugs treating chronic diseases. Second, the standardized German health insurance design does not feature a deductible, which could also explain stock-piling toward the end of the year (Einav et al., 2015). Third, physician budgets would suggest fewer and not more prescriptions toward the end of the budget period (which is end-December). Fourth, given the different procedures for buying a prescription drug and OTC cold remedies, it seems unlikely that chronically ill patients would pick up their prescription before buying flu treatment in November. For example, it would imply a visit to the neurologist (or geriatric doctor) to pick up a prescription for a chronic disease while suffering from the flu. Also, the density of pharmacies in Germany alleviates transaction costs for visits (1 pharmacy per 3,800 inhabitant). Fifth, an empirical test follows the economic intuition that state-dependency affects consumer choices in the current period as a function of decisions from previous periods (Shcherbakov, 2016). In particular, I estimate the following specification,

$$s_{jt} = \omega V_{jt} + \psi \hat{s}_{jt-1} + \epsilon_{jt}, \tag{7}$$

where s_{jt} are market shares of product j in period t. Exogenous variables, i.e., prices, product and period fixed-effects, are captured by V_{jt} and market shares from the previous periods, $\hat{s}_{jt-1}$, are instrumented with V_{jt-1}. In my data, patients buy a new drug package every 6 weeks on average. Therefore, the estimates test for the state-dependency of market shares lagged by two month. Table 6 presents the lagged coefficient for market shares, ψ, that are not different from zero. My results indicate absent state dependency in demand. Moreover, state dependency of demand might be an issue when switching poses medical risks at the curative treatment, which is not the case for AD drugs (NICE, 2011).

3.3 Identification and Estimation

The estimation strategy for the demand model in 3.2 follows the algorithm of Berry et al. (1995) and extends it in several dimensions (Reynaert and Verboven, 2014; Hess et al., 2006). Product fixed effects account for the simultaneity problem of the mean utility δ (Nevo, 2001). Therefore, the $\Delta\xi$ are mean independent of non-price attributes. I address the endogeneity of the structural model by using instrumental variables and estimate the

model with generalized method of moments (GMM). My moment conditions relate the structural error term, $\Delta\xi_{jt}$, and a set of instrumental variables:

$$E[\Delta\xi_{jt}|X_{jt}(\theta), Z_{jt}], \tag{8}$$

where $X_{jt}(\theta)$ contains all observable characteristics and Z_{jt} are instrumental variables.

First, variation of sales over time and changing choice sets (because of entry and exit) help to identify the random coefficient (σ) (Sovinsky Goeree, 2008). Additionally, I use optimal instruments in the sense of Chamberlain (1987), namely the expected value of derivatives of the unobserved quality of each product with respect to the parameter of the random coefficient σ:

$$z_{jt} = E[\frac{\partial\xi_{jt}(\alpha, \beta, \gamma, \sigma)}{\partial(\sigma)\prime}|x_{jt}]. \tag{9}$$

I follow the approximation of optimal instruments by Reynaert and Verboven (2014) where a first-stage with instrumental variables, Z_{jt}, predicts prices and derivatives of the mean utility are calculated with respect to the variance coefficient, σ, in the form $\frac{\partial\delta_{jt}(\hat{s_{jt}},\sigma)}{\partial\sigma}$. I follow Appendix A in Reynaert and Verboven (2014) to approximate for instruments under imperfect competition with a sample of $k = 1000$.

Second, if firms invest in OTC advertising to strategically influence prescription drug sales the endogeneity of advertising poses difficulties for identification. Also, I do not observe detailing (physician-directed advertising) which might be correlated with drug sales or consumer-directed advertising. I instrument advertising spillovers by exploiting seasonal illnesses, like colds, which are independent of the timing of the prescription drug market.

Third, as a cost-shifter for the supply side, I use crude oil prices (*Brent Europe*) from the *U.S. Energy Information Administration (EIA)* (Bresnahan, 1987). Crude oil is an important production input of pharmaceuticals and unlikely to be correlated with unobserved product-specific demand shocks. The instrument is interacted with active ingredients to increase its flexibility.

Fourth, I use traditional BLP-style instruments and construct the statistical means of product characteristics of competitors (Berry et al., 1995). The main assumption is that characteristics of products of competitors – and the product's location in the characteristics space – are exogenous. Endogenous quality choice of firms, e.g., the choice of product

characteristics in the short run (Crawford, 2012), is not an issue in the pharmaceutical industry since products are either an outcome of an uncertain investment in research or the result of regulatory changes, e.g., patent duration. In particular, I include the mean DDD per package of all competitors in the active ingredient class, the mean product age of all competitors, the mean package size of all competitors, and quadratic polynomials of all variables.

Table 7 presents results of the first-stage estimations. The coefficient of seasonality has a positive and statistically significant effect on advertising expenditures. Tests of the set of instrumental variables in the first stage confirm their strength, e.g., F-values of excluded instruments are 27 (prices) and 26 (advertising). Also, the tests for joint instrument significance are above the critical values (Stock et al., 2002). The market share from Equation 6 needs to be calculated numerically.[20] Own-price elasticities of market shares, s_{jt}, with respect to prices, p_{jt}, are calculated by:

$$\varepsilon^{p}_{jkt} \equiv \frac{\partial s_{jt}}{\partial p_{kt}} \frac{p_{kt}}{s_{jt}} = \begin{cases} \frac{p_{kt}}{s_{jt}} [\frac{1}{ns} \sum_{i=1}^{ns} (\alpha_{jt} + \nu_{ijt}\sigma^{opt}) s_{ijt}(1 - s_{ijt})] & \text{if } j = k \\ \frac{p_{kt}}{s_{jt}} [-\frac{1}{ns} \sum_{i=1}^{ns} (\alpha_{jt} + \nu_{ijt}\sigma^{opt}) s_{ijt} s_{ikt}] & \text{otherwise.} \end{cases} \tag{10}$$

The optimal value for σ from the BLP estimation is denoted σ^{opt}. Own- and cross-elasticities of market shares with respect to advertising are calculated by:

$$\varepsilon^{a}_{f(j)\tilde{f}(k)} \equiv \frac{\partial s_{jt}}{\partial a_{f(\tilde{k})t}} \frac{a_{f(\tilde{k})t}}{s_{f(k)t}} = \begin{cases} \gamma a_{f(j)t}(1 - \sum_{k \in f} s_{jt}) = \gamma a_t (1 - s_{jt}) & \text{if } f = \tilde{f} \\ \gamma a_{f(\tilde{k})t} s_{f(\tilde{j})t} & \text{otherwise.} \end{cases} \tag{11}$$

Since advertising expenditures vary by company, I calculate advertising elasticities by firms. Cross-advertising elasticities are calculated between $f(j)$ and $f(k)$, the firms owning product j and k.

3.4 Supply Side

I model the supply of prescription drugs as an oligopoly game where firms strategically choose prices and advertising expenditures. My analysis abstracts from entry and exit

[20] I use 5,000 pseudo-random draws using Modified Latin Hypercube Sampling (Hess et al., 2006) and 100 randomly sampled starting values to identify robust coefficients.

considerations and takes market structure as given.[21] The oligopoly models of imperfect competition seem to be a good fit for therapeutic drug markets where patented (originals and imports) and generic drugs compete for market shares (Dubois and Lasio, 2014; Kaiser et al., 2014; Dutta, 2011). High (sunk) fixed costs for research and development and moderate costs of production characterize the supply side of drug markets (Dutta, 2011).

Firms maximize profits by setting prices in the prescription drug market and advertising expenditures in the OTC market. The latter are freely set by firms depending on the marketing strategy of their OTC drug portfolio. I assume advertising as a fixed cost of production which is sunk after investment. Firms decide each period on their advertising stock. The model captures advertising stocks as the geometric sum of current and past advertising expenditures with the estimated optimal depreciation rate.

Profits of firms depend on revenues from all marketed products, including OTC drugs and non-medical drugs. I model revenues from the Alzheimer's disease prescription drug market. The market consists of F firms, each of which markets a subset $\mathcal{F}_f$ of the $j = \{1, ..., J\}$ drugs in market $t = \{1, ..., T\}$. The profit functions of multi-product firms f over prescription drugs are:

$$\Pi_{ft} = \sum_{j \in \mathcal{F}_{ft}} (p_{jt} - c_{jt}) M_t s_{jt}(\boldsymbol{p_t}, \boldsymbol{a_t}) - exp_{f(j)t} - C_{f(j)}, \tag{12}$$

where p_{jt} is the price of product j and c_{jt} the marginal costs of the same drug. Market shares are a direct function of all price vectors in time t, $\boldsymbol{p_t}$, and of all advertising stocks, $\boldsymbol{a_t}$. Advertising expenditures of firm $f(j)$ are denoted $exp_{f(j)t}$, total market size is M_t, and $C_{f(j)}$ are fixed costs of production.

After observing demand factors, firms maximize revenues by setting optimal prescription drug prices and advertising expenditures. In a pure-strategy Bertrand-Nash equilibrium, under the assumption of strictly positive support, every price for product j must satisfy the first-order condition:

$$s_{jt}(\boldsymbol{p_t}, \boldsymbol{a_t}) + \sum_{k \in \mathcal{F}_{f(j)t}} (p_{kt} - c_{kt}) \frac{\partial s_{kft}(\boldsymbol{p_t}, \boldsymbol{a_t})}{\partial p_{jt}} = 0. \tag{13}$$

[21] In the sample only generics and imports enter the market, which indicates regulation as being the main driver of market structure, e.g., patent duration or reference pricing.

Assumptions on the code of conduct of the pharmaceutical industry allow to derive markups $(p_{jt} - c_{jt})$ and marginal costs for every product.

3.5 Simulation

By comparing the simulated market outcome without advertising spillovers to the status quo, I explain how to quantify the economic effects of umbrella branding. In the counterfactual scenario the effects of umbrella branding are zero and prices are the only strategic variable of the firms. My assumption that other variables, including marginal costs and physician-directed advertising, are unaffected by the policy is in line with previous research (Nevo, 2001). The assumptions hold in the short run because firms cannot immediately adjust drug portfolios. If the ban of consumer-directed advertising result in higher spending on physician-directed advertising, I would overestimate the effect of an advertising ban. The counterfactual results are subject to the usual partial equilibrium critique.

Formally, the new price equilibrium, denoted by $\boldsymbol{p_t^0}$, must fulfill for all products j the first-order conditions:

$$s_{jt}(\boldsymbol{p_t^0}, 0) + \sum_{k \in \mathcal{F}_t} (p_{kt} - c_{kt}) \frac{\partial s_{kt}(\boldsymbol{p_t^0}, 0)}{\partial p_{jt}} = 0, \tag{14}$$

where advertising stocks are zero, $\boldsymbol{a_t} = 0$. Market shares for product j are given by:

$$s_{jt}(X^0, \boldsymbol{p_t^0}, 0; \theta) = \int_\nu \frac{\exp(\delta_{jt}^0 + \sigma p_{jt}^0 \nu_{ijt})}{1 + \sum_J \exp(\delta_{jt}^0 + \sigma p_{jt}^0 \nu_{ijt})} dP_{\nu_t}(\nu_t), \tag{15}$$

where $\boldsymbol{a_t} = 0$ and prices are optimal prices in the non-advertising state, $\boldsymbol{p^0}$. The set of product characteristics, X^0, does not contain advertising stocks. For the counterfactual price equilibrium, I solve for equations 14 and 15 numerically.

For the welfare calculation, I assume that patients choose products consistent with their underlying preferences. Advertising does not distort consumers and lead to choices inconsistent with utility maximization (Dubois et al., 2014). The coefficient for advertising can be interpreted as the valuation of the consumer for umbrella branding. Results of the simulated equilibrium and the estimated demand system are inputs for the approximation of consumer surplus. The monetary value of welfare changes due to the advertising ban

is calculated by the Hicksian compensation variation, measured by solving the integral over the differences in maximum expected utilities using numerical simulations (Small and Rosen, 1981; Kaiser et al., 2014):

$$CV_t = \int \frac{1}{\alpha + \nu_{it}} \left[ln \sum_j exp(\delta_{jt}^{pre} + \theta p_{jt}^{pre} \nu_t) - ln \sum_j exp(\delta_{jt}^{post} + \theta p_{jt}^{post} \nu_t) \right] dP_\nu(\nu_t) \quad (16)$$

where $\delta_{jt}^{post} = \delta_{jt}^0$ and $p_{jt}^{post} = p_{jt}^0$ are counterfactual equilibrium values for mean utility and prices. For a more complete welfare analysis, I report revenues and public health insurance expenditures for the two scenarios in the AD drug market. Formally, the change in producer surplus is defined as:

$$PS_t = (\boldsymbol{p_t} * \boldsymbol{q_t}) - (\boldsymbol{p_t^0} * \boldsymbol{q_t^0}) - mc_{jt} \quad (17)$$

and $\boldsymbol{p_t}$ and $\boldsymbol{q_t}$ are vectors of all prices and quantities $(\boldsymbol{s_t} * M_t)$.[22] Vectors from the counterfactual scenario are denoted $\boldsymbol{p_t^0}$ and $\boldsymbol{q_t^0}$.

4 Results

Results of the first column in Table 3, *Logit-IV*, assume homogeneous preferences of patients regarding prices. The specification uses instruments for prices and advertising to control for changes in unobserved product characteristics. Results show a negative price coefficient, i.e., price-sensitive consumers, and a positive coefficient for advertising spillovers.

The second column in Table 3 shows results of the random coefficient model and allows the individual disutility of prices. The mean price coefficient is negative and the random coefficient is .34 and is interpreted as the standard deviation from the mean valuation of prices. Table 3 presents median own-price elasticities of -1.28.[23] The coefficient for

[22] Advertising spending, exp_{ft}, affects the demand of all products of firm f, particularly of OTC drugs, and are part of the profit function. Since it is impossible to say what part of the advertising expenditure is accrued by the AD market, by assumption, $exp_{ft} = 0$ in the AD market. Advertising expenditures are fixed costs and are assumed to be sunk.

[23] Reference pricing (Kaiser et al., 2014) and tiered co-payments (Herr and Suppliet, 2017) result in price-sensitive behavior of patients. A generic market share of almost 70 percent constitutes a competitive generic market in Germany. My results are close to estimated own-price elasticities from other random

Table 3: Random Coefficient Logit Demand Results

	Logit Demand	
		random coeff.
Price	-1.56***	-2.14***
	(.09)	(.37)
RC Price		.34***
		(.10)
Advert.	.011***	.012***
	(.005)	(.005)
Originator	3.42***	3.30***
	(1.11)	(1.11)
Import	.79	.70
	(.83)	(.83)
Package Size	-.006	-.007
	(.006)	(.006)
Product Age	.01***	.01***
	(.003)	(.003)
Donepezil	7.76***	6.86***
	(.95)	(.95)
Galantamin	9.07***	8.11***
	(1.02)	(1.02)
Ginkgo Biloba	0.28	0.17
	(.62)	(.62)
Memantin	8.46***	7.50***
	(1.40)	(1.40)
Rivastigmin	9.81***	8.95***
	(1.08)	(1.08)
Own-price Elasticity (median)		-1.28
Advertising Elasticity (median)		.145
Product FE	yes	yes
Time FE	yes	yes
N	5,242	5,242
R^2_{adj}	.84	

Notes: Logit IV and Logit with random coefficients use instruments for prices and advertising, F-values of first stage regressions are x (price) and x (advert.). Taste coefficients for the characteristics are retrieved from a regression of the product fixed-effects on mean product attributes ($N = 106$, $R^2_{adj} = .78$) (Nevo, 2001). Elasticities for price and advertising are calculated based on formula 11 and 10. The estimation RC Logit uses 5,000 modified latin hypercube sampling draws to simulate market shares. Constant not reported. Robust standard errors are presented in parentheses; * $p < .1$, ** $p < .05$, *** $p < .01$.

umbrella branding is positive and statistically different from zero. The median elasticity of umbrella branding is .145.

All specifications comprise product and time fixed-effects. In empirical demand models with product fixed-effects, a minimum-distance procedure can identify taste parameters (Chamberlain, 1982) (see Appendix 5). I find that consumers put a higher value on drugs from originators and on some molecules, e.g., *galantanin* and *rivastigmin*. Utility increases for newer drugs and package size is not relevant.

4.1 Economic Effects of Umbrella Branding

Table 4 presents results of the effect of umbrella branding on prices, quantities, and welfare measures. The results stem from the simulation in section 3.5.

First, umbrella branding has an impact on the number of treated patients. About 10 percent more drugs are sold with advertising compared to the same market without advertising. Quantities of generics increase by about 6.5m daily doses and of originators by 1.5m. Changes for imports are negative and small. From a health policy perspective, the increase in daily doses might affect the health status of the population. In particular, the patient population of under-treated conditions would benefit from more medication, e.g., Alzheimer's disease patients (Sano et al., 2005). Generalizing the findings is difficult because the market expansion of overtreated drugs, e.g., by opioids (Alpert et al., 2017), harm the health status of patients.

Second, spillovers of advertising on the demand for prescription drugs increases the market shares of generic firms by approximately 25 percent and of originators by 3.4 percent (compared to the outside good). Firms with high expenditures for advertising benefit the most: the data shows that generic firms and originators possess stocks of advertising expenditures of, on average, €7.3m and €2.2m. The effect on market shares is negative for imports (-2.3 %). Patients seem to switch to the brand names that they know from consuming OTC drug advertising.

Third, price changes are small and positive for all drug types. Generic firms increase prices the most because they need to recover costly advertising, partially by higher prices. Most likely, originators have high margins which allow them to invest in advertising

coefficient logit demand models in pharmaceutical markets. Kaiser et al. (2014) report mean own-co-payment elasticities of -1.19, Chintagunta (2002) of -2.5, and Dubois and Lasio (2014) of -3.49.

Table 4: Effects of Umbrella Branding on Quantities, Prices, and Welfare

	All		Originators		Imports		Generics	
	w/o ad	Δ %	*w/o ad*	Δ %	*w/o ad*	Δ %	*w/o ad*	Δ %
Quantities (yearly sum, m)	78.8	10.08	45.8	3.41	7.52	-2.33	25.42	25.8
Price (mean) €, DDD)	1.41	.080	2.61	.073	2.59	.016	.420	.335
Health Insurance (sum, m)	230.6	5.87	185.9	4.90	28.5	-2.29	16.11	31.56
Revenues (yearly sum, m)	174.1	5.39	143.6	4.86	22.15	-2.29	8.39	34.84
Consumer Surplus: all Alzheimer patients, yearly, €						733,572		
Consumer Surplus: total public health insurance, yearly, €						48,691,059		

Notes: The table presents the effect of umbrella branding calculated by changes from the simulated equilibrium (no advertising spillovers) to the status quo. Absolute changes and percentage changes are reported. Mean values for monthly changes from Jan 2004 to Dec 2010. Estimated parameters of the random coefficient logit model are used to predict the counter-factual equilibrium.

without raising their prices by too large a sum. More intensive competition by advertising generics also helps to contain originators' prices.

Fourth, advertising spillovers into prescription drug markets increase the total expenditures of the public health insurance (including pharmacy reimbursement and sales tax) by about 5 percent. Although expenditures for generics increase by 30 percent, the total amount of €740k is a fraction of costs of originators' increases.

Fifth, on the supply side, revenues increase with advertising by an average of 5.3 percent. Firms sell more products with advertising and revenues from the Alzheimer's disease drug market increase by €3.3m.

Sixth, consumer surplus of umbrella branding is about €733k per year. AD drugs with advertising spillovers become more attractive compared to competing products without advertising and to the outside good. The consumer surplus is a trade-off between benefits from more treated (and healthier) patients and higher expenses of the public health insurance. The welfare effect is positive for the undertreated disease of AD and under the assumption of non-biased decision-making of consumers (Dubois and Lasio, 2014).

Seventh, direct advertising of Alzheimer's disease drugs with the molecule *ginkgo biloba* can have a market expansion effect through advertising spillovers on the drug class. Since I only observe firm-level advertising expenditures, I cannot disentangle the effect of direct advertising and umbrella branding on *ginkgo biloba*. However, I empirically test how its exclusion from the demand estimation affects the results (not reported). The advertising coefficient is positive, of similar magnitude, and statistically significant. Furthermore,

advertising for *ginkgo biloba* is small, e.g., the maximum share of advertising for *ginkgo biloba* is less than 1.8 percent of total OTC drug advertising expenditures (Nielsen Media, 2012).

5 Interpretation and Discussion

Umbrella branding links the reputation of firms across products. I show that umbrella branding across OTC and prescription drugs has a positive effect on sales of prescription drugs. The identification relies on the institutional setting of advertising regulation in Germany, a market that bans consumer-directed advertising of prescription drugs. Umbrella branding results in market expansion of about 733k daily doses per year. In particular, generic firms (that invest a lot in OTC drug advertising) benefit from a large effect on their aggregate sales.

The welfare effects based on the expansion of pharmaceutical markets should be evaluated with caution. Some therapeutic markets are already overtreated, such as with opioids, and a market expansion would be harmful to patients. Undertreated conditions, however, would benefit from more medicated patients, e.g., the Alzheimer's disease (Sano et al., 2005). For preventive therapies, the treatment of an acute outbreak can result in high costs. Health insurances might justify expenditures for additional preventive pharmaceuticals to avoid follow-up costs. Positive spillovers on prescription drugs imply more advertising in the OTC market than in an isolated market. Too much OTC advertising could result in more demand for OTC products and might, in extreme cases, result in adverse health effects. The possibility of the overuse of OTC drugs seems relatively unlikely since in Germany they consist largely of herbal molecules and low-dosage molecules.

If an effective ban of advertising is of interest to regulators, they might adapt the institutional design of drug market policies. Policymakers could cooperate to adapt guidelines for drug packaging, for example, the *Federal Trade Commission* (*FTC*) and the *FDA*. If similarity of product names or the umbrella branding of a product portfolio confuses patients, clear guidelines for product packaging and marketing could ultimately assist consumers. The existence of spillovers urges the development of guidelines for drug labeling, for example, the display of active ingredients on the package (ISMP, 2015).

Another aspect is the strategic implication for firms. For example, in some markets, like the AD drug market, the advertising effects might be larger for generic firms than

for originators. As a policy to promote generic substitution, regulators could promote the advertising of generic drug manufacturers in order to increase their market shares.

Moreover, some originators, such as *Pfizer*, have been in the market for several decades while others are newly established brand names, e.g., through mergers. For example, Bronnenberg et al. (2012) find long-lasting effects of brand capital for consumer goods in supermarkets. To disentangle the effects of established brand names and of advertising in the pharmaceutical industry is a promising topic for future research.

References

Alpert, Abby, David Powell, and Rosalie Liccardo Pacula, "Supply-Side Drug Policy in the Presence of Substitutes: Evidence from the Introduction of Abuse-Deterrent Opioids," *NBER Working Paper 23031*, 2017.

Avery, Rosemary J., Matthew Eisenberg, and Kosali I. Simon, "The impact of direct-to-consumer television and magazine advertising on antidepressant use," *Journal of Health Economics*, 2012, *31* (5), 705–718.

Azoulay, Pierre, "Do Pharmaceutical Sales Respond to Scientic Evidence?," *Journal of Economics & Management Strategy*, 2002, *11* (4), 551–594.

Bagwell, Kyle, "The Economic Analysis of Advertising," in M. Armstrong and R. Porter, eds., *Handbook of Industrial Organization*, number 28. In '3.', Elsevier, 2007, pp. 1701–1844.

Balachander, Subramanian and Sanjoy Ghose, "Reciprocal Spillover Effects: A Strategic Benefit of Brand Extensions," *Journal of Marketing*, 2003, *67* (1), 4–13.

Berndt, E., L. Bui, D. Reiley, and G. Urban, "Information, marketing, and pricing in the US antiulcer drug market," *American Economic Review*, 1995, *85* (2), 100–105.

Berndt, Ernst R and Joseph P Newhouse, "Pricing and Reimbursement in US Pharmaceutical Markets," in S. Nicholson P.M. Danzon, ed., *The Oxford Handbook of the Economics of the Biopharmaceutical Industry*, OUP USA, 2012, pp. 201–265.

Berndt, Ernst R., Robert S. Pindyck, and Pierre Azoulay, "Consumption Externalities and Diffusion in Pharmaceutical Markets: Antiulcer Drugs," *The Journal of Industrial Economics*, 2003, *51* (2), 243–270.

Berry, Steven, James Levinsohn, and Ariel Pakes, "Automobile Prices in Market Equilibrium," *Econometrica*, 1995, *63* (4), 841–890.

Bhattacharya, Jayanta and William Vogt, "A Simple Model of Pharmaceutical Price Dynamics," *Journal of Law and Economics*, 2003, *46* (2), 599–626.

BMG, "Facts and Figures," `http://www.bmg.bund.de/krankenversicherung/zahlen-und-fakten-zur-krankenversicherung.html` [accessed 22 January 2015] 2015.

Bresnahan, Timothy F, "Competition and collusion in the American automobile industry: The 1955 price war," *The Journal of Industrial Economics*, 1987, *35* (4), 457–482.

Bronnenberg, Bart J and Jean-Pierre Dubé, "The Formation of Consumer Brand Preferences," *Annual Review of Economics*, forthcoming.

_ , **Jean-Pierre H Dubé, and Matthew Gentzkow**, "The evolution of brand preferences: Evidence from consumer migration," *The American Economic Review*, 2012, *102* (6), 2472–2508.

Cabral, L M B, "Stretching firm and brand reputation," *RAND Journal of Economics*, 2000, *31* (4), 658–673.

Carrera, Mariana, Dana Goldman, Geoffrey Joyce, and Neeraj Sood, "Do physicians respond to the costs and cost-sensitivity of their patients?," *forthcoming American Econonomic Journal: Economic Policy*, 2017.

Caves, R. E., M. D. Whinston, and M. A. Hurwitz, "Patent expiration, entry, and competition in the US pharmaceutical industry," *Brookings Papers on Economic Activity. Microeconomics*, 1991, pp. 1–66.

Chaloupka, Frank J and Kenneth E Warner, "The Eonomics of Smoking," in Thomas G. Mcguire Mark V. Pauly and Pedro P. Barros, eds., *Handbook of Health Economics*, Vol. 1, Elsevier, 2000, pp. 1539–1627.

Chamberlain, Gary, "Multivariate regression models for panel data," *Journal of Econometrics*, 1982, *18* (1), 5–46.

_ , "Asymptotic efficiency in estimation with conditional moment restrictions," *Journal of Econometrics*, 1987, *34* (3), 305–334.

Ching, Andrew and Masakazu Ishihara, "The effects of detailing on prescribing decisions under quality uncertainty," *Quantitative Marketing and Economics*, 2010, *8* (2), 123–165.

_ , **C. Robert Clark, Ignatius J. Horstmann, and Hyunwoo Lim**, "The Effects of Publicity on Demand: The Case of Anti-Cholesterol Drugs," *Marketing Science (forthcoming)*, 2015.

Ching, Andrew T and Masakazu Ishihara, "Measuring the informative and persuasive roles of detailing on prescribing decisions," *Management Science*, 2012, *58* (7), 1374–1387.

Chintagunta, Pradeep K, "Investigating Category Pricing Behavior at a Retail Chain," *Journal of Marketing Research*, 2002, *39* (2), 141–154.

Choi, Jay Pil, "Brand extension as informational leverage," *The Review of Economic Studies*, 1998, *65* (4), 655–669.

Crawford, Gregory S., "Endogenous product choice: A progress report," *International Journal of Industrial Organization*, 2012, *30* (3), 315–320.

_ **and Matthew Shum**, "Uncertainty and Learning in Pharmaceutical Demand," *Econometrica*, 2005, *73* (4), 1137–1173.

Degam, "Dementia Guideline 12," `http://www.degam.de/files/Inhalte/Leitlinien-Inhalte/Dokumente/DEGAM-S3-Leitlinien/LL-12_Langfassung_TJ_03_korr_01.pdf` [accessed 12 February 2015] 2015.

DGPPN, "S3-Leitlinie Demenzen," `https://www.dgppn.de/fileadmin/user_upload/_medien/download/pdf/kurzversion-leitlinien/s3-leitlinie-demenz-kf.pdf` [accessed 12 February 2015] 2015.

Donohue, Julie M, Marisa Cevasco, and Meredith B Rosenthal, "A decade of direct-to-consumer advertising of prescription drugs.," *The New England Journal of Medicine*, 2007, *357* (3), 673–681.

Dubé, Jean Pierre, Günter J. Hitsch, and Puneet Manchanda, "An empirical model of advertising dynamics," *Quantitative Marketing and Economics*, 2005, *3* (2), 107–144.

Dubois, Pierre and Laura Lasio, "Identifying Industry Margins with Unobserved Price Constraints: Structural Estimation on Pharmaceuticals," *CEPR Discussion Paper 9881*, 2014.

_ **, Rachel Griffith, and Martin O'Connell**, "The Effects of Banning Advertising on Demand, Supply and Welfare: Structural Estimation on a Junk Food Market," *CPER Discussion Paper 9942*, 2014.

Dunn, Abe, "Drug innovations and welfare measures computed from market demand: The case of anti-cholesterol drugs," *American Economic Journal: Applied Economics*, 2012, *4*, 167–189.

Duso, Tomaso, Annika Herr, and Moritz Suppliet, "The Welfare Impact of Parallel Imports: A Structural Approach Applied to the German Market for Oral Antidiabetics," *Health Economics*, 2014, *23* (9), 1036–1057.

Dutta, Antara, "From Free Entry to Patent Protection: Welfare Implications for the Indian Pharmaceutical Industry," *Review of Economics and Statistics*, 2011, *93* (1), 160–178.

Einav, Liran, Amy Finkelstein, and Paul Schrimpf, "The response of drug expenditure to nonlinear contract design: evidence from medicare part D," *The Quarterly Journal of Economics*, 2015, *130* (2), 841–899.

Erdem, Tülin, "An Empirical Analysis of Umbrella Branding," *Journal of Marketing Research*, 1998, *35* (3), 339–351.

_ **and Baohong Sun**, "An Empirical Investigation of the Spillover Effects of Advertising and Sales Promotions in Umbrella Branding," *Journal of Marketing Research*, 2002, *39* (4), 408–420.

EUC, "Pharmaceutical Sector Inquiry," *Technical Report*, 2009.

Eurocode, "The EUROCODE (European Collaboration on Dementia) Project," `http://www.alzheimer-europe.org/Alzheimer-Europe/Our-work/Completed-projects/2006-2008-EuroCoDe` [accessed 10 July 2015] 2015.

FDA, "Best Practices in Developing Proprietary Names for Drugs: Guidance for Industry," `http://www.fda.gov/downloads/drugs/guidancecomplianceregulatoryinformation/guidances/ucm398997.pdf` [accessed 20 December 2014] 2014.

Garthwaite, Craig L, "Demand spillovers, combative advertising, and celebrity endorsements," *American Economic Journal: Applied Economics*, 2014, *6* (2), 76–104.

Goldberg, Pinelopi Koujianou and Rebecca Hellerstein, "A structural approach to identifying the sources of local currency price stability," *The Review of Economic Studies*, 2013, *80* (1), 175–210.

Hakenes, Hendrik and Martin Peitz, "Umbrella branding and external certification," *European Economic Review*, 2009, *53* (2), 186–196.

Herr, Annika and Moritz Suppliet, "Cost-sharing and drug pricing strategies: Introducing tiered co-payments in reference price markets," *forthcoming Journal of Health Economics*, 2017, pp. 1–32.

Hess, Stephanie, Kenneth E. Train, and John W. Polak, "On the use of a Modified Latin Hypercube Sampling (MLHS) method in the estimation of a Mixed Logit Model for vehicle choice," *Transportation Research Part B*, 2006, *40* (2), 147–163.

Hilger, James, Greg Rafert, and Sofia Villas-Boas, "Expert opinion and the demand for experience goods: an experimental approach in the retail wine market," *Review of Economics and Statistics*, 2011, *93* (4), 1289–1296.

Hurwitz, Mark A and Richard E Caves, "Persuasion or information? Promotion and the shares of brand name and generic pharmaceuticals," *Journal of Law and Economics*, 1988, *31* (2), 299–320.

Iizuka, T, "What Explains the Use of Direct-to-Consumer Advertising of Prescription Drugs?," *The Journal of Industrial Economics*, 2004, *52* (3), 349–379.

Iizuka, T. and G. Z. Jin, "Direct to consumer advertising and prescription choice," *Journal of Industrial Economics*, 2007, *55* (4), 571–772.

IMS Health, "Alzheimer's Disease Drugs 2004-2010," *PharmaScope National database*, 2012.

ISMP, "Protecting US Citizens from Inappropriate Medication Use," `http://www.ismp.org/pressroom/viewpoints/CommunityPharmacy.pdf` [accessed 15 March 2015] 2015.

Kaiser, Ulrich, Susan J. Mendez, Thomas Rønde, and Hannes Ullrich, "Regulation of pharmaceutical prices: Evidence from a reference price reform in Denmark," *Journal of Health Economics*, 2014, *36* (1), 174–187.

Kesternich, Iris, Heiner Schumacher, and Joachim Winter, "Professional norms and physician behavior: homo oeconomicus or homo hippocraticus?," *Journal of Public Economics*, 2015, *131*, 1–11.

Königbauer, Ingrid, "Advertising and generic market entry," *Journal of Health Economics*, 2007, *26* (2), 286–305.

Kravitz, Richard, Ronald Epstein, Mitchell Feldman, Carol Franz, Rahman Azari, Michael Wilkes, Ladson Hinton, and Peter Franks, "Influence of Patients' Requests for Direct-to-Consumer Advertised Antidepressants," *Journal of the American Medical Association*, 2005, *293* (16), 1995–2002.

Lakdawalla, Darius, Neeraj Sood, and Qian Gu, "Pharmaceutical advertising and Medicare Part D," *Journal of Health Economics*, 2013, *32* (6), 1356–1367.

Larkin, Ian, Desmond Ang, Jonathan Steinhart, Matthew Chao, Mark Patterson, Sunita Sah, Tina Wu, Michael Schoenbaum, David Hutchins, Troyen Brennan et al., "Association between academic medical center pharmaceutical detailing policies and physician prescribing," *Journal of the American Medical Association*, 2017, *317* (17), 1785–1795.

Lasio, Laura, "Delisting of Pharmaceuticals from Insurance Coverage: Effects on Consumption, Pricing and Expenditures in France," *mimeo*, 2015.

Ling, Davina C., Ernst R. Berndt, and Margaret K. Kyle, "The Long Shadow of Patent Expiration, Generic Entry, and Rx-to-OTC Switches," *Journal of Law and Economics*, 2002, *45* (S2), 691–723.

Mizik, Natalie and Robert Jacobson, "Are physicians easy marks? Quantifying the effects of detailing and sampling on new prescriptions," *Management Science*, 2004, *50* (12), 1704–1715.

Murry, Charles, "Advertising in Vertical Relationships: An Equilibrium Model of the Automobile Industry," *mimeo*, 2015.

Nelson, Phillip, "Advertising as information," *Journal of Political Economy*, 1974, *82* (4), 729–754.

Nevo, Aviv, "Measuring market power in the ready-to-eat cereal industry," *Econometrica*, 2001, *69* (2), 307–342.

NICE, "A NICE-SCIE Guideline on supporting people with dementia and their carers in health and social care," *National Clinical Practice Guideline No. 42*, 2011.

Nielsen Media, "OTC Drugs," *White Paper*, 2012.

OECD, "Value for Money in Health Spending," *OECD Health Policy Studies*, 2010.

Prasad, Raekha, "Alcohol use on the rise in India," *The Lancet*, 2009, *373* (9657), 17–18.

Qaseem, Amir, Vincenza Snow, J Thomas Cross Jr, Mary Ann Forciea, and Robert Hopkins Jr, "Current Pharmacologic Treatment of Dementia: A Clinical Practice Guideline from the American College of Physicians and the American," *Annals of Internal Medicine*, 2008, *148* (5), 370–378.

Reiffen, David and Michael R. Ward, "Branded generics as a strategy to limit cannibalization of pharmaceutical markets," *Managerial and Decision Economics*, 2007, *28* (4-5), 251–265.

Reynaert, Mathias and Frank Verboven, "Improving the performance of random coefficients demand models: The role of optimal instruments," *Journal of Econometrics*, 2014, *179* (1), 83–98.

Rizzo, J A, "Advertising and Competition in the Ethical Pharmaceutical Industry: The Case of Antihypertensive Drugs," *The Journal of Law and Economics*, 1999, *42* (1), 89–116.

Sano, Mary, Joan Amatniek, Morgan Feely, Feliks Sinyak, Denise Holton, Steve Ascher, and Sanford I Finkel, "Undertreatment of patients with Alzheimer's disease in an elderly United States population.," *Alzheimer's & Dementia: the Journal of the Alzheimer's Association*, 2005, *1* (2), 136–144.

Schwermann, Tim, Wolfgang Greiner, and JM Schulenburg, "Using disease management and market reforms to address the adverse economic effects of drug budgets and price and reimbursement regulations in Germany," *Value in Health*, 2003, *6* (s1).

Shapiro, Bradley T, "Positive Spillovers and Free Riding in Advertising of Prescription Pharmaceuticals: The Case of Antidepressants," *Journal of Political Economy*, forthcoming.

Shcherbakov, Oleksandr, "Measuring consumer switching costs in the television industry," *The RAND Journal of Economics*, 2016, *47* (2), 366–393.

Shum, Matthew, "Does advertising overcome brand loyalty? Evidence from the breakfast-cereals market," *Journal of Economics & Management Strategy*, 2004, *13* (2), 241–272.

Small, Kenneth A. and Harvey S. Rosen, "Applied Welfare Economics with Discrete Choice Models," *Econometrica*, 1981, *49* (1), 105–130.

Sovinsky Goeree, Michelle, "Limited Information and Advertising in the U.S. Personal Computer Industry," *Econometrica*, 2008, *76* (5), 1017–1074.

Stock, James H, Jonathan H Wright, and Motohiro Yogo, "A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments," *Journal of Business & Economic Statistics*, 2002, *20* (4), 518–529.

Tirole, Jean, "A theory of collective reputations (with applications to the persistence of corruption and to firm quality)," *The Review of Economic Studies*, 1996, *63* (1), 1–22.

Wernerfelt, Birger, *The Rand Journal of Economics*, 1988, *19* (3), 458–466.

Winslow, Bradford, Mary Onysko, Christian Stob, and Kathleen Hazlewood, "Treatment of Alzheimer disease," *American Family Physician Guideline*, 2011, *83* (12), 1403–1412.

Wosinska, Marta, "Direct-to-Consumer Advertising and Drug Therapy Compliance," *Journal of Marketing Research*, 2005, *42* (3), 323–332.

APPENDIX A

Taste Parameters and Brand Fixed Effects

Nevo (2001) and Goldberg and Hellerstein (2013) suggest projecting the vector of brand dummy coefficients from the demand estimation (Equation 3) onto product characteristics. Formally, the term d denotes the product dummy coefficients, X the matrix of time-invariant product characteristics such as package size, import label, drug age, concentration, and molecule. ξ are unobserved product characteristics. From the individual patient utility function follows:

$$d_j = X_j\beta + \xi_j. \tag{18}$$

The assumption $E[\xi_j|X_j] = 0$ allows us to estimate $\hat{\beta}$, the taste parameters for product characteristics (Nevo, 2001). The assumption originates in previous work to rationalize instrumental variables, e.g., Berry et al. (1995). I collapse product characteristics at the product-level.

Figures and Tables

Figure 2: *Bayer* OTC drug example (Bayer sales 2014: €12bn)

Figure 3: *Bayer* Prescription drug example (Bayer sales 2014: €4.3bn)

Table 5: Umbrella Branding of Top-20 Advertising Drug Firms in Germany

Rank	Firm	mean [€, m]	min	max	Product Portfolio	AD Drug
1	MCM Klosterfrau	4,978,668	458,345	14,600,000	OTC only	x
2	Bayer	4,732,136	1,554,209	10,400,000	Prescription drugs & OTC	
3	Novartis	2,709,205	370,886	6,035,431	Prescription drugs & OTC	x
4	Pfizer	2,464,615	31,753	6,304,846	Prescription drugs & OTC	
5	Dr. Willmar Schwabe	2,137,257	176,662	4,099,485	OTC only	x
6	GlaxoSmithKline	1,870,835	37,836	5,424,186	Prescription drugs & OTC	
7	Hexal	1,772,860	116,966	6,510,396	Prescription drugs (generics) & OTC	x
8	Spitzner	1,574,603	11,506	3,986,249	OTC only	
9	ratiopharm	1,461,147	83,859	4,135,006	Prescription drugs (generics) & OTC	x
10	Medice	1,014,186	19,504	4,136,447	Prescription drugs (generics) & OTC	
11	Merck	854,170	188,509	2,677,581	Prescription drugs & OTC	
12	Stada	849,239	21,160	2,556,131	Prescription drugs (generics) & OTC	x
13	Dr. Wolff	677,134	0	3,673,007	OTC only	
14	Sandoz	391,700	0	1,886,998	Prescription drugs (generics) & OTC	x
15	Roche	361,922	240,017	2,022,806	Prescription drugs & OTC	
16	Salus	300,848	6,778	1,236,721	Prescription drugs (generics) & OTC	x
17	Verla	296,582	700	1,009,387	Prescription drugs (generics) & OTC	x
18	Winthrop	252,490	0	1,604,827	Prescription drugs (generics) & OTC	
19	Merz	224,413	0	1,143,847	Prescription drugs (generics) & OTC	x
19	Berlin Chemie	192,002	8,969	687,431	Prescription drugs & OTC	

Notes: The column Product Portfolio indicates if firms sell prescription and OTC drugs under the same brand name. This table presents the top-20 firms in total OTC drug market advertising from 2004 to 2010. Own calculation with data from Nielsen. ***One of Johnson & Johnson's subsidiaries, Janssen-Cilag, is a prescription drug manufacturer but does not advertise under the J&J brand.

Table 6: Test for State Dependency

s_{jt-2}	.312
	(.189)
p_{jt}	-.001**
	(<.01)
Product FE	yes
Time FE	yes
N	4,938
R^2_{adj}	.96

Notes: This table presents results for the test on state dependency as suggested in Shcherbakov (2016). The dependent variables are market shares (in daily doses sold) and prices are in € and per daily dose. Constant not reported. Standard errors in parentheses are clustered on the product level. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 7: First-stage Results Demand Results

	Price	Advertising
Seasonality	.006	4.391***
	(.01)	(.48)
No. products other ATC5	.075***	-.072
	(.01)	(.11)
Package size (own nest, mean)	.017***	.324***
	(.00)	(.02)
Package size (other nests, mean)	.046***	.577***
	(.00)	(.06)
DDD (other ATC7, mean)	-.056***	-.041
	(.00)	(.05)
DDD (other ATC7 & firm, mean)	.001	-.057
	(.00)	(.03)
DDD (own firm, mean)	.135***	-.980*
	(.03)	(.40)
DDD (own nest, mean)	1.493***	1.378
	(.13)	(1.06)
Age (own nest, mean)	.140	-.200
	(.08)	(.95)
Quantity (own firm, mean)	-.112***	-.160
	(0.02)	(0.27)
Crude oil × Donepezil	yes	yes
Product FE	yes	yes
Time FE	yes	yes
$F-test$ excl. IV	27.07	26.95
N	5,242	5,242

Notes: First-stage estimation results for price and advertising stock. Constant not reported. Robust standard errors are presented in parentheses; * $p < .1$, ** $p < .05$, *** $p < .01$.